Dynamic Bayesian decision network to represent growers' adaptive pre-harvest burning decisions in a sugarcane supply chain*

C. S. Price
University of KwaZulu-Natal
and CSIR Meraka Centre for Artificial Intelligence Research
Private Bag X54001
4000 Durban
South Africa
pricec@ukzn.ac.za
ORCID 0000-0002-8749-7253

D. Moodley
University of Cape Town
and CSIR Meraka Centre for Artificial Intelligence Research
Private Bag X3
7701 Rondebosch
South Africa
deshen@cs.uct.ac.za
ORCID 0000-0002-4340-9178

A. W. Pillay
University of KwaZulu-Natal
and CSIR Meraka Centre for Artificial Intelligence Research
Private Bag X54001
4000 Durban
South Africa
pillayw4@ukzn.ac.za
ORCID 0000-0001-7160-6972

ABSTRACT

Sugarcane growers usually burn their cane to facilitate its harvesting and transportation. Cane quality tends to deteriorate after burning, so it must be delivered as soon as possible to the mill for processing. This situation is dynamic and many factors, including weather conditions, delivery quotas and previous decisions taken, affect when and how much cane to burn. A dynamic Bayesian decision network (DBDN) was developed, using an iterative knowledge engineering approach, to represent sugarcane growers' adaptive pre-harvest burning decisions. It was evaluated against five different scenarios which were crafted to represent the range of issues the grower faces when making these decisions. The DBDN was able to adapt reactively to delays in deliveries, although the model did not have enough states representing delayed delivery statuses. The model adapted proactively to rain forecasts, but only adapted reactively to high wind forecasts. The DBDN is a promising way of modelling such dynamic, adaptive operational decisions.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; *Knowledge representation and reasoning*; Probabilistic reasoning, Reasoning about belief and knowledge • **Mathematics of computing** → **Probability and statistics**; *Probabilistic representations*; Bayesian networks, Decision diagrams

KEYWORDS

Dynamic Bayesian decision network, adaptive operational decisions, cognitive model, sugarcane grower, burning and harvesting sugarcane

ACM Reference format:

C. S. Price, D. Moodley and A. W. Pillay 2018. Dynamic Bayesian network to represent growers' adaptive pre-harvest burning decisions in a sugarcane supply chain. *In 2018 Annual Conference of the South African Institute of Computer Scientists and Information Technologists (SAICSIT 2018), September 26-28, 2018, Port Elizabeth, South Africa*.

DOI: 10.1145/3278681.3278693

1 INTRODUCTION

The sugar supply chain is made up of two parts: the sugarcane supply chain and the distribution chain [1]. In the sugarcane supply chain, the sugarcane is grown and transported to the mill, whereas in the distribution chain, the stabilised raw sugar product is transported to markets and other processors [1]. The sugarcane supply chain is particularly complex [2, 3], due to biophysical challenges that include varying weather conditions; different soils; and variation in crop growth; and the many participants in the chain [4].

An agent-based simulation was developed to model the transport complexities of a KwaZulu-Natal (KZN) sugarcane supply chain [5]. In this model, the grower agents harvested cane daily without taking into account uncertainties such as the weather, how much

SAICSIT '18, September 26–28, 2018, Port Elizabeth, South Africa

ACM ISBN 978-1-4503-6647-2/18/09...$15.00
https://doi.org/10.1145/3278681.3278693

cane they had already harvested, or how far behind they were with their deliveries. All these factors make growers' harvesting decisions complex and dynamic. Growers need to adapt their pre-harvest burning decisions to their current situation, e.g. how much cane is currently ready to be transported, and whether deliveries are on target or behind. This situation changes over time, depending on which decisions were previously taken. Growers also need to anticipate the effects of uncertain weather events, for example rain or high winds, which would disrupt harvesting and therefore delivery. This complexity and dynamism needs to be modelled so that a more realistic cognitive model of the grower's decisions can be included in the simulation model.

Recent work on farmers' operational decisions, such as pre-harvest burning, shows that farmers do not make operational decisions or plans once and then implement that plan daily [6]. Rather, they make a partial plan that moves them towards some goal, monitor progress towards the goal, and change the plan continuously [7-9]. They make decisions based on uncertain information, unexpected events (e.g. a storm, or equipment breaking down), their own experience and expertise, as well as their goals, constraints and preferences [7]. Farmers' decisions tend to be flexible, giving room for choosing future alternatives [6], especially with respect to the weather [10]. They make decisions which can be adapted to different circumstances [8]. They anticipate likely events and uncertainties and include those in their plans, but if an unexpected event occurs, they adapt their plans to respond to the new situation [6].

When modelling such uncertain and complex domains, Bayesian decision networks (BDNs) have been used [11, 12], but these models do not take changes over time into account. However, dynamic Bayesian decision networks (DBDNs) extend BDNs to represent change over time. This paper investigates and evaluates DBDNs as a modelling and inference tool to represent the adaptive and dynamic way that sugarcane growers make pre-harvest burning decisions. To our knowledge, models of sugarcane growers' adaptive pre-harvesting burning decisions have not been developed to date.

The layout of this paper is as follows: first, a literature review describing Bayesian networks, their use in agriculture and sugarcane supply chains is given. Factors affecting the grower's pre-harvest burning decisions are also provided. This is followed by the methodology which outlines how the DBDN was developed and evaluated. The description of the developed model is followed by its evaluation. Finally conclusions and future work are outlined.

2 LITERATURE REVIEW

2.1 Bayesian networks

Bayesian networks are useful formalisms for representing cause-effect relationships under uncertainty [11, 13]. Bayesian networks are directed acyclic graphs [13]. This means that they cannot have feedback loops. In Bayesian networks, chance nodes represent variables. Each node has two or more discrete, mutually exclusive and exhaustive states [11]. Each node contains a conditional probability table (CPT) which contains the probability of each of the states occurring. The nodes are linked with directed arcs, which represent a cause-effect relationship [11]. The causal arrows between nodes also reflect how humans think [14].

Making inputs into a Bayesian network is called recording evidence. Evidence can be entered in one or more nodes at any time, and the evidence will replace the *a priori* CPT values [15]. As one enters evidence, the Bayesian network updates the likelihoods of each of the states of the nodes using the conditional probability tables [11]. This is called inference or belief updating. This means that after inputting one or more pieces of evidence, the state of the whole system can be determined [16]. Bayesian networks obey the Markov property in that each node is only dependent on the nodes to which it is linked [11]. This simplifies the inference calculations [11].

Bayesian networks have been extended with decision and utility nodes to represent decision making under uncertain conditions [11, 13]. These Bayesian decision networks (BDNs), or Influence Diagrams, assume that all of the data needed for the decision is known before making the decision. A disadvantage of BDNs is that they do not allow feedback loops so they cannot represent how the network changes over time.

Not allowing feedback loops has been rectified in dynamic Bayesian networks (DBNs), which are Bayesian networks where the static Bayesian network is repeated for a number of time slices [11, 17]. The network also has inter-slice arcs which show how variables from one time slice affect variables in the next time slice. Dynamic Bayesian decision networks (DBDNs) build on DBNs, in that they include decision and utility nodes [17]. The DBDN can thus be used to represent an adaptive decision making process.

2.2 Models of operational farm decision making

In agricultural settings, BDNs have been used for many strategic agricultural decisions [6, 18, 19]. However, they do not reflect the adaptive nature of how farmers actually make daily decisions, especially in dynamic environments [6, 20].

In their review of adaptation in farm decision-making models, Robert *et al.* [6] noted that farmers tend to make static plans which could incorporate uncertainties, and dynamic decisions which would adapt to a shock or other circumstances. They found that recursive models and discrete stochastic programming were used to represent both dynamic and static decision making processes. Bayesian networks (or any extensions thereof) were not mentioned by Robert *et al.* [6] as a possible formalism for representing these types of operational decisions.

In addition, none of the models reviewed by Robert *et al.* [6] modelled farmers' harvesting decisions. This is probably because in most other crops, the harvesting period is shorter, so is less likely to be affected by weather events as harvesting the sugarcane crop is.

2.3 Use of BNs in sugarcane supply chains

In the sugarcane arena, Everingham *et al.* [21] and Shongwe [22] have proposed Bayesian updating to help predict long term sugarcane yields and shredder breakdowns at the mill respectively. Drury *et al.* [23] have proposed text mining to generate a BN of factors influencing sugarcane yield. In the literature generally, the development of DBDNs is scarce. For example, in the medical field, DBDNs have been proposed to represent decisions over time [24, 25]. However, no DBNs or DBDNs were found relating to the sugarcane supply chain or growers' pre-harvest burning decisions.

2.4 Factors affecting pre-harvest burning decisions for sugarcane growers

The sugarcane harvesting season is a relatively long one, compared to other agricultural crops [26]. In KwaZulu-Natal, South Africa, cane is harvested from mid-March to October/November [27]. This means that weather, particularly rainfall, can and does play a disruptive part in harvesting the cane and transporting it to the mill [26-29]. As cane is generally burned before it is harvested, high winds can also disrupt the harvesting process if there are runaway fires [27]. If cane is too wet when it is burned, the grower will be transporting leaves and cane to the mill, instead of just cane [28, 29].

The decision of how much cane to burn is challenging for the grower. Firstly, uncertainty must be taken into account. There is uncertainty regarding the weather, and the grower's belief of what the weather will actually be like, given the weather forecast. The grower also needs to take into account his belief in how dry the cane is. Secondly, growers need to be flexible in their decision making. In the sugarcane supply chain setting, growers anticipate impending rains or wind in their burning decisions by sometimes burning more than one day's delivery quota in advance [29]. However, if there is a long period of soft soaking rain which makes the cane too wet to burn [22, 27, 30], they make decisions to catch up with their deliveries once the cane is dry enough to burn. The third challenge in the burning decision is the time factor. Growers need to deliver a consistent volume of cane to the mill each week of the milling season. Some mills impose penalties if this is not done. In addition, growers cannot burn too much cane at one time, because the cane's quality declines on burning [31]. Delivering cane which was burned more than 72 hours beforehand to the mill can risk penalties of loss of income to the grower, especially if cane quality is used as one of the factors in determining the cane price at the mill. In making the burning decision, the grower will try to mitigate these risks.

3 METHODOLOGY

Growers and the cane procurement manager of a KwaZulu-Natal mill were interviewed to learn their decision rules and understand how their cane deliveries worked. The necessary ethical clearance was granted[2].

The iterative knowledge engineering approach to creating Bayesian networks [11] was used to develop the DBDN. There are three main ways of constructing a Bayesian network. The network can be created manually, it can be generated from data, or a combination of both [19]. Manual construction involves engaging experts and stakeholders to help build the network. Published papers can also be used to inform the structure and/or conditional probabilities [12].

In this study, the hybrid approach was used. The structure of the "weather" part of the network (wind, maximum temperature and rain) was designed manually. Daily weather data from 1 Jan 1998 to 31 Dec 2015 for the mill area were downloaded from the SASA weather portal [32]. Weather data for the next day were added to the spreadsheet by phase shifting the existing data by one day. Pearsons correlation tests were performed to ensure that each of the weather variables were not correlated [33]. The CPTs of the weather variables were imported using Netica [34]'s Expectation Maximisation algorithm. Based on interviews with the mill's cane procurement manager and growers, the rainfall CPTs were adjusted to reflect whether the rain was drizzle or thundershower: in the summer months (December to March), for low daily rainfalls of 0.1-4mm, half was assumed to be thundershowers and the other half was assumed to be drizzle. Amounts of rain over 4mm was assumed to be thundershowers. For the rest of the year, all low amounts of daily rain (0.1-4mm) were assumed to be drizzle, while amounts >4mm were assumed to be thundershowers.

The network was then imported to Hugin ver 7.8 [35] to allow the creation of more than 15 nodes, and the structure of the DBDN was developed by hand by the first author, based on interviews with the mill's cane procurement manager and growers and literature. Node and state names were checked for vagueness [33] and edited if necessary. States were checked that they covered the full range of possible values of a node [11, 36]. The second author checked the DBDN structure. The remaining CPTs were compiled by hand by the first author. Based on the interviews, literature and own assumptions [12], the following initial set of rules guided the completion of the CPTs:

- cane would not be burned if it was wet;
- cane would also not be burned if there were high winds;

[2] Ethical clearance HSS/0204/101.

- cane could be burned if it were damp and the grower was behind with deliveries;
- if drizzle or thundershowers were forecast for a particular day, the grower could still burn that day if the cane were dry;
- the cane dryness recovers fast after thundershowers, but soft soaking drizzle which lasts a few days leaves the cane wet;
- wet or damp cane dries based on the maximum temperature and the wind;
- cane could be burned and harvested in exactly integer multiples of the day's delivery quota;
- growers could deliver up to two day's cane delivery quota on one day; and
- if cane was burned, then it could also be harvested and delivered on the same day.

The convergent and discriminant validity of the network [36] was checked by searching the literature for examples of BNs (or extensions thereof) relating to farming, sugarcane, weather, and harvesting decisions.

The predictive validity [36] of the DBDN was tested by adding evidence for all the combinations of variables for a two time slice version of the network. Adjustments to the CPTs were made where necessary. A number of different scenarios were then tested for more time slices, each testing different combinations and complexities of the network (case based evaluation [11]). A set of five scenarios were crafted to demonstrate the different types of complexity the model needed to address, and represent the range of different types of issues that the grower faces when making the burning decision. The scenarios are:

1. Baseline scenario: May weather: low wind, medium temperature, no rain; dry cane, deliveries on target
2. Similar to scenario 1, except that deliveries are behind; they caught up, but became behind again due to cane not being delivered
3. Spring: Drizzle is forecast. Cane becomes wet.
4. August: high wind, high temperatures
5. Using actual weather data from October 2016, with damp cane.

Scenario 1 gives a baseline situation, where weather does not interrupt burning decisions, and deliveries are on track. Scenario 2 keeps the same weather conditions, but investigates how the grower catches up with delayed deliveries. Scenario 3 introduces wet weather – particularly drizzle – which is problematic for KwaZulu-Natal sugarcane supply chains. Scenario 4 looks at how high levels of wind would affect the burning decision. Finally, scenario 5 uses actual weather data for a rainy period in October 2016 to evaluate how the model responds. The network was then evaluated against these scenarios.

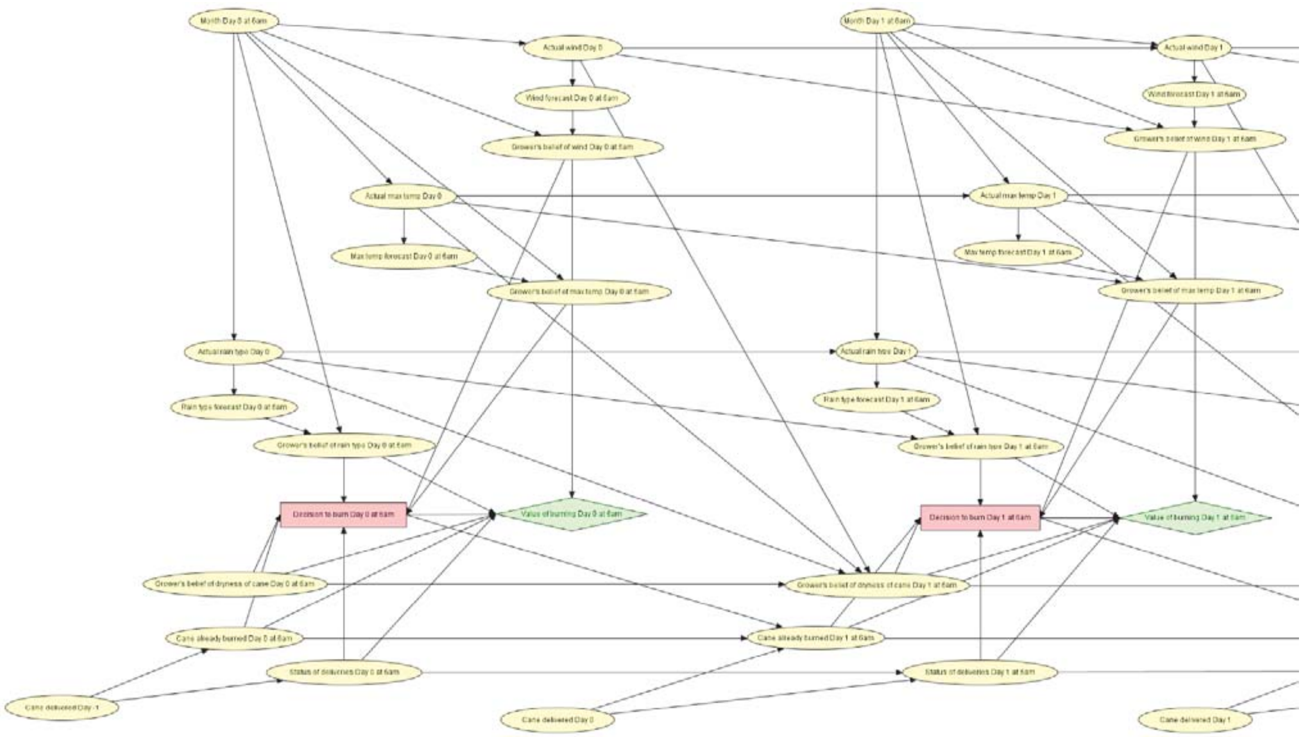


Figure 1: DBDN for deciding how much cane to burn each day (two time slices)

Table 1: Nodes (and their states) which affect the burning decision

Grower's belief of wind Day n	Grower's belief of maximum temperature Day n	Grower's belief of rain type Day n	Grower's belief of dryness of cane Day n
10 to 110 (low)	5 to 22 (low)	No rain	Dry
110.1 to 180 (medium)	22.1 to 27 (medium)	Thundershower	Damp
180.1 to 560 (high)	27.1 to 45 (high)	Drizzle	Wet

Cane already burned Day n	Status of deliveries Day n	Decision to burn Day n
No cane burned	On target	Don't burn cane
1 day's cane burned	1 day behind	Burn 1 day's cane
2 day's cane burned	2 days behind	Burn 2 day's cane
3 day's cane burned	More than 2 days behind	Burn 3 day's cane

4 DBDN MODEL

Two time slices of the DBDN for representing a sugarcane grower's burning and harvesting decisions is shown in Figure 1 on the previous page. It is assumed that the burning decision for a particular day is taken early in the morning (e.g. 6am). Factors affecting the burning decision (see Table 1) are:

- the grower's belief of the wind, maximum temperature and rain type, given the forecast for the day and the month
- the grower's belief of the dryness of cane
- the amount of cane already burned
- the status of deliveries (on target or behind)

The continuous weather data were categorized into three states (see Table 1). Wind is measured in average wind run in km per day (the total amount of wind in km that was experienced at a particular place) and maximum temperature in ^{0}C. The grower's belief of the dryness of cane is affected by the dryness of cane on the previous day, as well as the previous day's actual weather (wind, maximum temperature and rain type). The amount of cane already burned on one day depends on the amount of cane that was burned on the previous day less the amount delivered by the end of the previous day. Sugar mills often have a rule that growers may not deliver cane that is older than 72 hours due to cane quality degradation [31]. Mills also have rules preventing growers from over-delivering (delivering in advance), to ensure fairness amongst all the growers, hence the worst delivery state being "More than 2 days behind".

5 RESULTS AND DISCUSSION

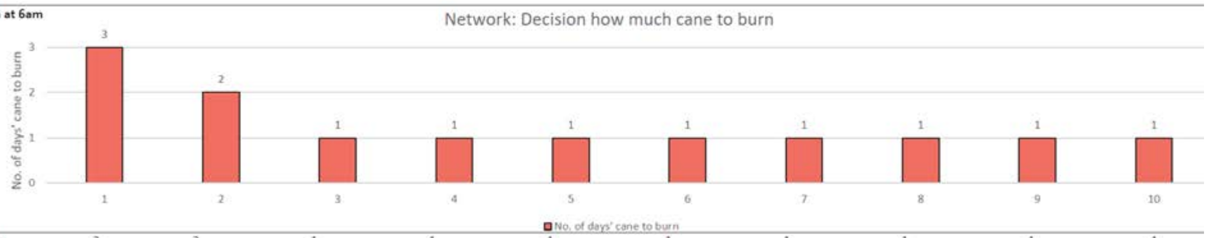
5.1 Scenario 1 (base scenario): Low wind, medium temperature, no rain, dry cane, deliveries are on target

The first scenario describes weather that does not pose a challenge to burning: low wind, medium maximum temperature, no rain. This is typical of May and June. In this case, too, the deliveries are on target, no cane is already burned, and the grower believes that the cane is dry. After having entered the inputs for Day 1,

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
Grower's belief of weather at 6am	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain	Low wind, medium max temp, no rain
Grower's belief of dryness of cane at 6am	Dry	Dry	Dry	Dry	Dry	Dry	Dry	Dry	Dry	Dry
Cane already burned at 6am	0	1	1	0	0	0	1	2	1	0

Status of deliveries at 6am

Decision to burn at 6am



	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
No. of days' cane actually burned	3	2	1	1	1	1	1	1	1	1
Days cane delivered by end of day	2	2	2	1	1	0	0	2	2	1

Figure 2: Scenario 2 results. Catching up on deliveries, not delivering (days 6 & 7) and catching up again

the network suggests that the grower should burn 1 day's cane. The grower then takes the advice to burn 1 day's cane. The weather on day 1 was the same as the grower's belief of the weather.

On the next day (day 2), the grower enters his beliefs of the weather for the day, as well as the amount of cane delivered on the previous day (1 day's cane – i.e. what was burned and harvested on the previous day was delivered on that day too). The network then deduces that the cane is dry, that there is no cane already burned, and that the status of deliveries is on target. Similar to the previous day, the network suggests burning 1 day's cane. If the network's suggestions are accepted and entered as evidence into the network for all the following days, and what is burned is delivered, the burning decision remains to burn 1 day's cane. With all the same values, the network will consistently advise burning 1 day's cane. This is as expected.

5.2 Scenario 2: Deliveries are behind, caught up and became behind again

Throughout scenario 2 (see Figure 2 on the previous page), the weather remains the same (low wind, medium maximum temperature and no rain). Cane is believed to be dry and there is no cane already burned. However, deliveries start out more than two days behind. Since deliveries are behind, a drastic measure of burning 3 day's cane occurs on day 1, two of which are delivered. 2 day's cane is then burned the next day, followed by 1 day for the rest of the scenario. By delivering 2 day's cane on days 2 and 3, deliveries are back on track by day 4. However, deliveries are not made on days 6 and 7, so deliveries are behind again, but caught up by day 10.

This scenario shows the adaptability of the burning decision to deliveries. It should be said, though, that if deliveries are behind and no deliveries are made, the network will continue to suggest that one day's cane be burned – to keep up with deliveries (not shown in Figure 2). However, this will be problematic if no deliveries are made for a number of days as the cane quality will degrade, and cane older than 3 days will not be accepted at the mill. In this case, the grower/user would have to keep track of the age of the cane, as well as the quantity already burned each day.

5.3 Scenario 3: Drizzle is forecast; cane becomes wet

In scenario 3 (see Figure 3), the weather changes over the days. The cane starts out dry. The evidence entered into the "Grower's belief of dryness of cane" node is shown above the "Network: Belief of dryness of cane graph". The amount of cane already burned is shown under this, followed by the network's decision to burn. The actual number of days' cane that were burned is shown

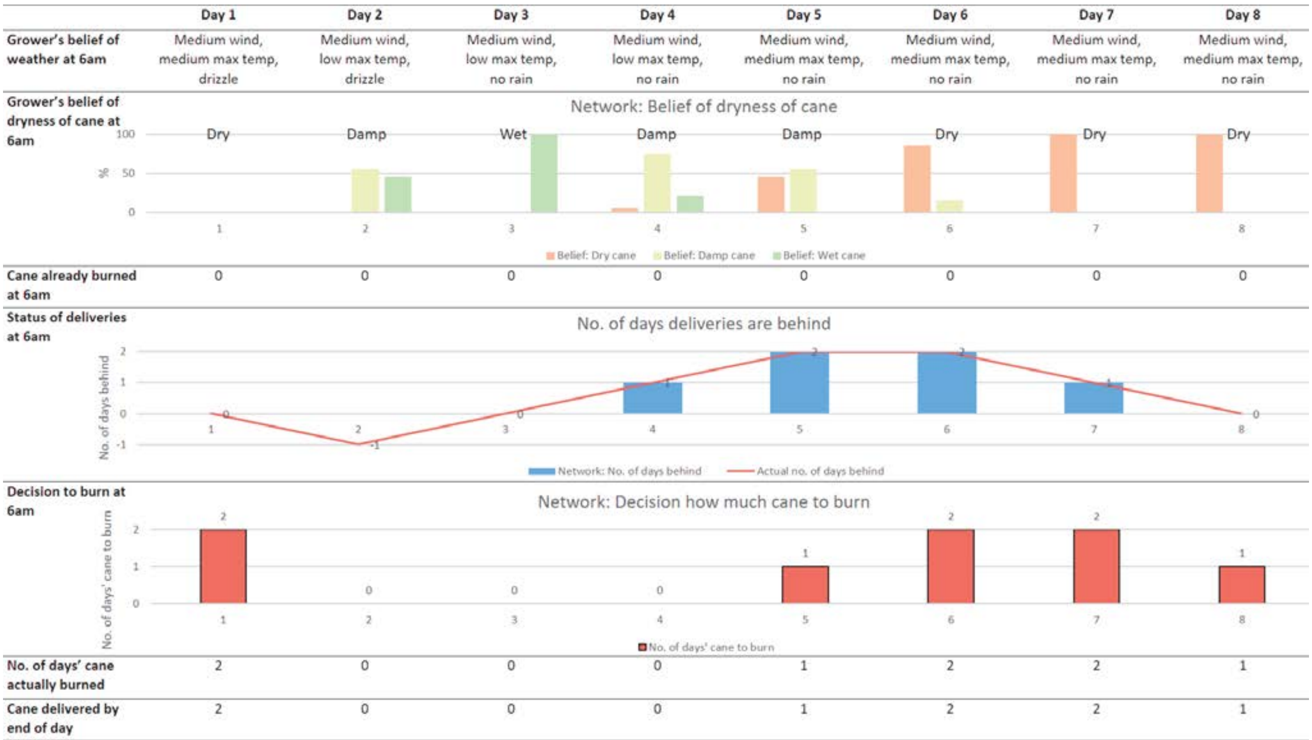


Figure 3: Scenario 3 results. Cane is dry, and drizzle is forecast; cane becomes wet and eventually dries out

in the row below. The amount of cane actually delivered is shown in the last row.

On day 1, drizzle is forecast, and materializes. With the drizzle forecast, the network correctly suggests that more cane than normal (2 day's delivery quota) should be burned to mitigate the effect of the wet weather. This means that the grower is one day ahead (i.e. -1 days behind), but there is no state to recognize this in the "Status of deliveries" node. When it drizzles for two days (days 1 and 2), the cane becomes damp, then wet. It takes another two days to dry out. As a result, burning, harvesting and deliveries are delayed. The network behaves as expected here; burning cane in advance of a spell of wet weather is a common practice [29]. At another mill in the KwaZulu-Natal midlands, it was found that it took the mill five days to recover from a rain event [27], which is similar to what is shown in Figure 3.

5.4 Scenario 4: High wind, high temperatures

Scenario 4 shows what occurs when Berg winds (hot dry winds) are forecast. In this scenario, the cane is dry, there is no cane already burned, and deliveries are on target (see Figure 4). Because high winds are forecast, and the grower believes the forecast, he does not burn cane that day. In fact he has to wait until the wind dies down – in this case until day 3. At that point, he is able to catch up with burning and delivery activities.

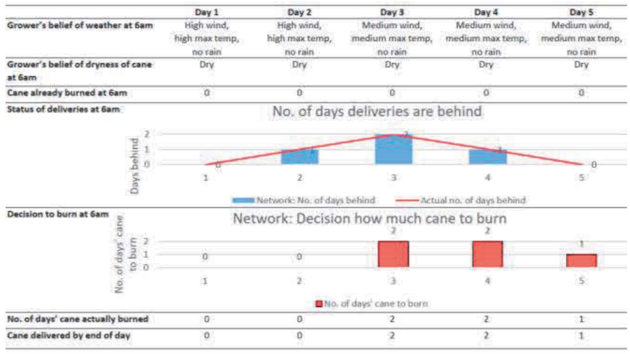


Figure 4: Scenario 4 results. High winds forecast

The grower does not burn in high wind due to the threat of runaway fires [29-31]. However, in this case, the network is not behaving as the grower would: normally the grower would be scanning the forecasts days ahead, and would be making adjustments based on his belief of the upcoming weather. However, with DBDNs, the Markov property states that one can only access nodes from the current and previous time slices, so in this instance, the network makes the grower fall further behind than he would have normally been.

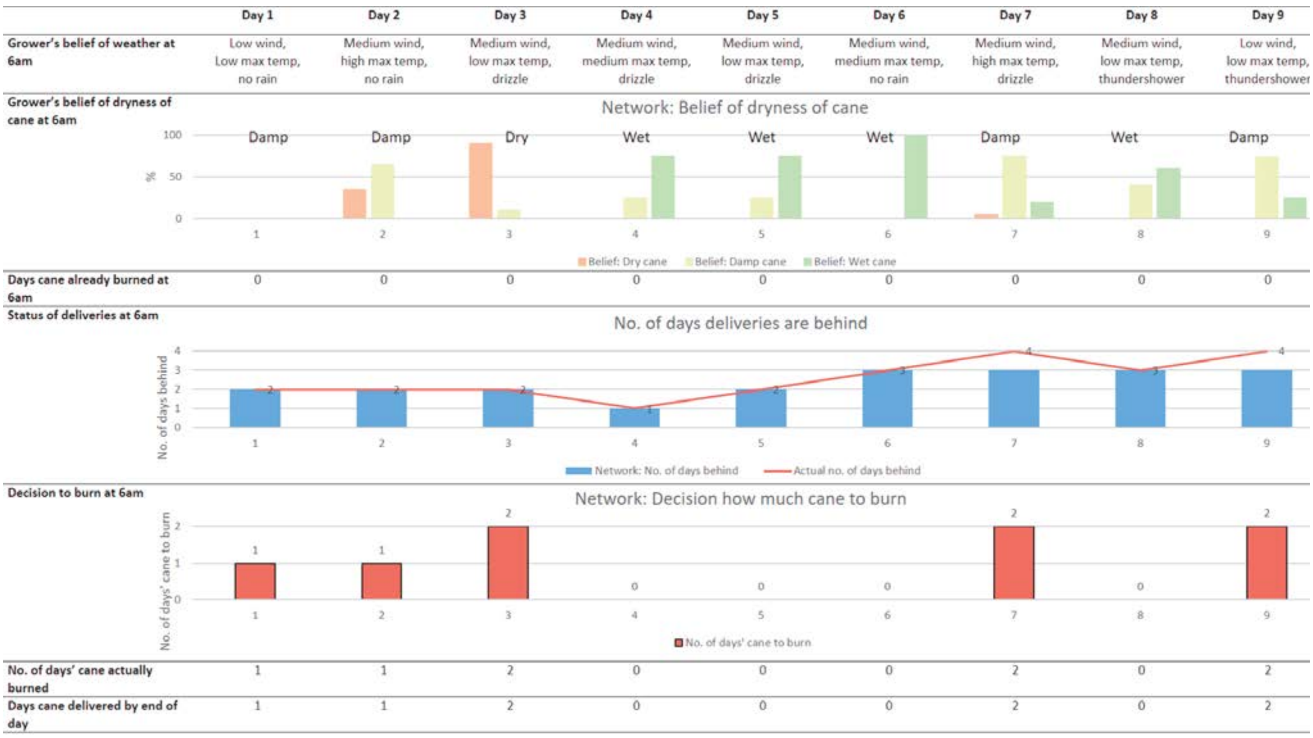


Figure 5: Scenario 5 results. Actual weather 5 to 13 October 2016 was used. Cane started out damp.

5.5 Scenario 5: Using October 2016 weather data

For scenario 5, actual weather data for 5 to 13 October 2016 for the mill area was entered into the network (see Figure 5 on the previous page). As there had been rain before 5 October, it was assumed that the cane was damp. Throughout this scenario, there was no cane already burned at the beginning of each day. The status of deliveries was generally behind. On days 4 and 8, deliveries caught up a bit, but lapsed due to the persistent wet weather. The network recorded that deliveries were "More than 2 days behind", whereas in fact they were 4 days behind by day 9. On days 1, 2 and 7, cane was burned in spite of the fact that it was damp. This was allowed because deliveries were behindhand. This situation of not being able to burn cane, and therefore not deliver, is common during the days of extended rainfall [28] which is commonly experienced in the springtime [31]. In fact, rainfall events have a widespread effect on the sugarcane supply chain as a whole [28, 29].

5.6 Discussion

The DBDN adjusts and adapts burning decisions appropriately to most weather conditions; the belief of the dryness of the cane; how much cane is already burned at the time of making the decision; and the delivery status.

5.6.1 Weather. The DBDN correctly anticipates impending drizzle by burning two day's cane so that deliveries can continue to some extent during the wet weather. When berg wind conditions (i.e. high wind and high temperature) are forecast, the model correctly suggests that one should not burn that day, for fear of runaway fires. However, in reality, growers would have anticipated such conditions on previous days, and would have burned in advance of berg winds so that deliveries could continue in spite of the high winds. Because of the Markov property where one can only use information for that day and the previous day, the DBDN is not able to represent this grower behavior.

5.6.2 Status of deliveries. If the grower's opinion of cane is dry, and deliveries are behind, the decision to burn node keeps on suggesting that the grower should burn cane (to catch up). However, if there is a problem with the transport to the mill, or the mill has stopped working (e.g. breakdown or maintenance), the grower should override the decision to burn by not burning, and keep track of how many days behind he actually is with deliveries.

There are not enough states in the "Status of deliveries" node to reflect exactly how many days behind with deliveries the grower is. The node measures up to two days behind, and anything more than that is classified as "More than 2 days behind". The decision to burn treats this last state as if it were representing three days behind. The grower (or user of the network) needs to remember how many days behind he is, and if it's more than two days, consistently choose the "More than two days behind" state until deliveries are more on track (i.e. 2 or fewer days behind). In addition, one could be in the "1 day ahead" state, as was demonstrated in the 3rd scenario.

While the DBDN does predict the cane already burned, given the previous day's deliveries, and to some extent the status of deliveries, there are no checks built into the model to ensure that the user records a plausible amount of cane delivered on the previous day. For example, if there was no cane already available yesterday and 1 day's cane was burned, there is no safety net to force the user to select either 1 or 0 day's cane as being delivered yesterday.

5.6.3 Cane quality. The DBDN merely gives an indication of how much cane is already burned at the start of the day. It does not keep track of when that cane was burned. For example, 3 day's cane burned three days ago is regarded as equivalent to 3 day's cane burned yesterday, or 1 day's cane burned the day before yesterday and 2 day's cane burned yesterday. This means that the grower needs to keep track of the cane quality as well as the status of deliveries. If it should occur that deliveries were not possible, cane would have to be abandoned, and the grower (or user) would have to override the amount of cane already burned at the beginning of the day.

5.6.4 Harvesting. The DBDN does not explicitly model the harvesting of the cane, e.g. labor/machine availability. It is also known that in wet weather, fields can be inaccessible [27], which further delays the delivery process. However, these issues are not covered in this model.

Table 2: Evaluation of scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Uncertainty	✓	✓	✓	✓	✓
Proactive adaptiveness	NA	NA	✓	✕	✓
Reactive adaptiveness	NA	✓	–	✓	–
Dynamism	✓	✓	✓	✓	✓
Represents grower's experience, goals, constraints, preferences	✓	✓	✓	✓	✓

5.6.5 Evaluation of the scenarios. A summary of the scenarios and characteristics for evaluation can be seen in Table 2. The DBDN is suitable for representing decisions based on uncertain information, for example, the grower's belief of the weather, and of the dryness of cane. The first two scenarios did not lend themselves to proactive adaptiveness, but scenarios 3 and 5 showed how the grower anticipated the imminent rain and burned more cane in advance. However, scenario 4 (see Figure 4) did not fare well with proactive adaptiveness, as there was not enough warning for the farmer to burn before the strong wind materialized (see Table 2). On the reactive adaptiveness score, scenarios 2 and 4 reacted well and caught up the delayed deliveries, which is what a grower would aim to do. Scenarios 3 and 5 also attempted to catch up with delayed deliveries, but did not do well with the representation of the status of deliveries (one day ahead, or more than two days behind). The grower would typically know the status of his deliveries. If he inserted the correct values into the network as evidence, the model would work as expected. More states for being ahead could be added to the model (e.g. 1 day ahead, 2 days ahead). However, if considering adding more states representing the lateness of deliveries, it is unclear how many would be needed. By the end of scenario 5, the grower was four days behind, but in fact rain continued for the rest of October and November in 2016. This is a particularly pertinent issue, as each additional state means that many more conditional probabilities need to be obtained for the decision table.

All five scenarios showed dynamism in that the decision took different time steps into account, letting the variables for time $t+1$ be affected by the variables for time t. In addition, in all five scenarios, the model represents the grower's experience, goals, constraints and preferences: these are reflected in the conditional probability tables and the utilities of the model.

5.6.6 Design decisions and tradeoffs. When representing the way humans make decisions, the DBDN has marked advantages over the normal (static) BDN, in that the latter assumes that all the information needed for the decision is at hand, and the decision will be made once. With DBDNs, the process followed by humans when making daily decisions is more closely matched. As different information becomes available, the decision can be adapted to the new circumstances.

Where data was available, it was used to populate the CPTs. Unfortunately, there were many CPTs which needed to be completed manually. Business rules were used to generate CPTs to keep them consistent.

When designing this model, it was realized that the harvesting decision actually started with a decision to burn the cane. The burning decision is the more complex part of the harvesting decision, so this aspect was emphasized in the model. Other aspects of harvesting can be added later, using the iterative knowledge engineering approach [11].

The DBDN model presented and evaluated here shows that this formalism is a promising way of representing dynamic and adaptive decision making. This initial model needs several enhancements, for example, finding a way of proactively adapting to long-term weather forecasts; increasing the number of states representing the status of deliveries; and reducing the number of arcs entering the decision node [33, 37]. In addition, the model needs to be evaluated by the growers at the mill [36].

6 CONCLUSIONS

When making daily operational decisions, humans, and in this case sugarcane growers, do not make a decision once and implement it [8]. Rather, they aim for a goal, start working towards it, and monitor where they have got to, and adjust where necessary [8]. The DBDN is an apt modeling formalism to use to model this dynamic and adaptive decision making.

A DBDN was used to model the burning decisions taken by a sugarcane grower prior to harvesting. The model represented uncertainty, dynamism and the grower's experience, goals, constraints and preferences well. When rain was expected, the model proactively adapted the burning regime to the wet weather. It was not as good at adapting proactively to high winds. The model reactively adapted to delays in delivery by catching up (or trying to do so). However, if deliveries were over two days behind, the grower (or the model user) would have to remember exactly how many days behind, and override what the model suggested. Overall, DBDNs are a promising approach to representing such adaptive and dynamic decisions.

The contributions of the paper are the DBDN which represents the complex and dynamic decisions taken by the grower; and the evaluation of the model. DBDNs are not commonly cited or used in the literature, and to our knowledge, no one has proposed using them for modelling growers' pre-harvest burning decisions or anything else relating to the sugarcane supply chain. This kind of model could be considered for other operational dynamic adaptive decisions in the farming domain, as the DBDN represents a series of decisions, as highlighted by Daydé *et al.* [8].

Future work includes further model refinement, model validation with stakeholders, and using this model in an agent-based simulation of the sugarcane supply chain [5], where this decision making model will be incorporated into the cognitive mechanism of a grower agent.

ACKNOWLEDGMENTS

The authors gratefully thank: the cane procurement manager, the mill and growers of the KwaZulu-Natal sugarcane supply chain; and the CSIR Meraka Centre for Artificial Intelligence Research (CAIR) and the University Capacity Development Programme (UCDP) for the funding which contributed to this research. The first author thanks: Prof. C.N. Bezuidenhout for the introduction to sugarcane supply chains; and the College of Law and Management Studies (UKZN) and the Quilling family for writing retreats, during which time part of the Bayesian network was developed.

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